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EXPLORING THE VALUE OF ONLINE REVIEWS TO ORGANIZATIONS: IMPLICATIONS FOR REVENUE FORECASTING AND PLANNING

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Extended Abstract¹

One of the most intriguing social phenomena brought forth by advances in information and communication technologies is the vast amplification of the power of word-of-mouth. With the help of the Internet, wireless networking, and mobile telephony, today's citizens and consumers are forming a bewildering array of technology-mediated communities where they exchange opinions and experiences on companies, products, services, and even world events.

Word-of-mouth is arguably a phenomenon as old as society itself. Nevertheless, the advent of the Internet has added two important new dimensions to this timeless concept:

- *Unprecedented scalability and speed of diffusion.* Information technologies enable opinions of a single individual to instantly reach thousands or even millions of consumers. This escalation in audience is changing the dynamics of many industries in which word of mouth has traditionally played an important role. For example, the entertainment industry has found that the rapid spread of word of mouth is shrinking the lifecycles of its products (movies) and causing it to rethink its pre- and post-launch marketing strategies (Muñoz 2003). In fact, movies are seeing much more rapid change in revenues between the opening weekend and second weekend, suggesting that public opinion is spreading faster.²
- *Persistence and measurability.* In offline settings, word-of-mouth disappears into thin air. In online settings traces of word-of-mouth can be found in many publicly available Internet forums, such as review sites, discussion groups, chat rooms, and Web logs. This public data provides organizations with the ability to quickly and accurately measure word-of-mouth *as it happens* by mining information available on Internet forums.

¹**Keywords:** Online reviews, motion pictures, revenue forecasting, diffusion models

²Rick Sands, the chief operating officer at Miramax, summarized this trend by stating that, "In the old days...you could buy your gross for the weekend and overcome bad word of mouth, because it took time to filter out into the general audience. Those days are over. Today, there is no fooling the public" (Muñoz 2003).

Rapid measurement is the first prerequisite for the fast *reactions* that are needed in this new playing field. Nevertheless, the information value of online forums to organizations is currently not well understood. There is controversy related to the reliability of online reviews as well as to how well these reflect the opinions of the population of consumers. Anecdotal evidence suggests that some of this information may be biased and is sometimes provided anonymously by the companies themselves (Harmon 2004; White 1999). Finally, even though the impact of online reviews on consumer behavior has been the focus of recent research (Chevalier and Mayzlin 2003; Sénécal and Nantel 2004), there is very little work on how such information can be used by *firms* to gain business advantage.

This paper addresses firm usage of publicly available online word of mouth data by studying the information value of online movie reviews in forecasting motion picture revenues. We focused on the motion picture industry because word of mouth plays an important role and because online movie reviews are readily available. Inspired by the Bass model of product diffusion, we develop a notably accurate revenue forecasting model that is based on statistics of online movie reviews posted during the first week of a new movie's release.

In contrast with some previous motion picture revenue forecasting literature (Eliashberg and Shugan 1997), the thesis of this paper is not that online movie reviews *influence* future revenues, but rather that online movie reviews constitute a *measurable proxy* for word of mouth that can be exploited by studios for revenue forecasting and planning. To our knowledge, we are the first to provide positive evidence for this question.

Related Work

Our work relates and contributes to three important streams of past research: forecasting models of motion picture revenues, diffusion models of new product adoption, and methodologies for measuring word-of-mouth.

Forecasting models of motion picture revenues. Predicting the success of a motion picture has largely been viewed in the industry as a wild guess (Litman and Ahn 1998). Despite such difficulty, several researchers have attempted to develop predictive models forecasting movie revenue (for a review of such models, see Litman 1998). Such models can be classified along two main methodological dimensions: (1) quantitative/econometric models that focus on factors that predict or influence motion picture revenue (Elberse and Eliashberg 2002; Litman 1983; Litman and Ahn, 1998; Litman and Kohl 1989; Neelamegham and Chintagunta, 1999; Ravid, 1999; Sochay 1994); and (2) behavioral models that focus on factors involved in individual decision making towards selecting a movie to watch (De Silva 1998; Eliashberg et al. 2000; Eliashberg and Sawney, 1994; Sawney and Eliashberg, 1996; Zufryden, 1996). Notably missing from most studies is a consideration of the impact of word-of-mouth. Our study thus extends previous quantitative work on drivers of motion picture revenues by incorporating measurable proxies of word-of-mouth in forecasting box-office revenues and by examining the relative predictive power of such variables compared to more established variables such as critics' reviews and marketing expenditures.

Diffusion models of new product adoption. The impact of word of mouth on product sales was first examined by Bass (1969). The Bass model is a classic model of new product diffusion that incorporates the impact of mass media and interpersonal communication. The model has been shown capable of predicting the growth pattern of a wide range of new products with minimal data. The Bass model has spawned a huge literature of theoretical and empirical work. Many extensions to the model have been proposed. For excellent literature surveys, see Mahajan et al. (1990, 2000). We contribute to the diffusion literature by proposing a novel extension of the original Bass model that includes a time discounting factor for word of mouth. Time discounting captures the fact that a consumer's intensity of interpersonal communication about a product is highest immediately following the time of adoption and tends to die out over time.

Methodologies for measuring word-of-mouth. Traditional attempts to measure word of mouth are based on two principal techniques: inference and surveys. The advent of the Internet introduced a third technique for measuring word of mouth: directly through Usenet groups and feedback forums. Researchers can gather large amounts of data from online feedback forums. Previous research has used *volume* and *dispersion* when examining online word of mouth (Godes and Mayzlin 2002). The theory behind measuring dispersion, or the spread of communication across communities, is that word of mouth spreads quickly within communities, but slowly across them (Granovetter 1973). The theory behind volume is that the more consumers discuss a product, the higher the chance that other consumers will become aware of it. In this study we extend previous attempts to measure the impact of online word-of-mouth by experimenting with additional measures such as the *valence* (e.g. the average rating of a movie), *density* (e.g. the fraction of consumers who feel compelled to provide online feedback), and *time evolution* of online feedback.

Data Set

Data for this study were collected from Yahoo! Movies (<http://movies.yahoo.com>), BoxOfficeMojo.com (<http://www.boxofficemojo.com>), and The-Numbers.com (<http://www.the-numbers.com>). From Yahoo! Movies, we collected the names of all movies for the year 2002; this gave us a total of 2,942 titles. For the purpose of our analysis, we excluded all titles that fall in one or more of the following categories: (1) not released in the United States, (2) not a theatrical release (VHS, DVD, etc.), (3) not a nation-wide release. We were left with 474 movies, the total number of nationally released movies in 2002. For each of these titles, we collected detailed rating information from Yahoo! Movies, including all of the critic reviews (score and review text) and all user reviews (date and time of review, rating, review text). We were also able to get somewhat noisy demographic information (gender, age) about each of the individual reviewers from the information attached to the associated Yahoo IDs.

We used Boxofficemojo.com and The-numbers.com to obtain weekly box office, budget, and marketing expenses data. This information was missing for several movies from the publicly accessible parts of those sites. We obtained a data set of 128 movies with complete production, weekly box office, and daily user review data. We further trimmed this data set to only include movies for which at least 10 user ratings were posted during the first week of release. Our final data set consists of 80 movies, 1,188 weekly box office data, 1,040 critic reviews (an average of 13 reviews per movie), and 55,156 user reviews from 34,893 individual users. Of particular interest to our model are user reviews posted during the first week of a movie's release. Our data set contains an average of 312 first week user reviews per movie (minimum 12, maximum 3,802).

Forecasting Model

Our revenue-forecasting model assumes that the evolution of a movie's revenues follows a modified Bass equation:

$$\dot{R}(t) = (N - R(t))(p\delta^t + q \int_{k=0}^t \dot{R}(t-k)\delta^k dk), \quad 0 < \delta < 1 \quad (1)$$

In equation (1), t represents elapsed time since a movie's nationwide release, $R(t)$ is the *cumulative* revenue generated until time t , $\dot{R}(t)$ is the rate of revenue increase at time t , and N is a measure of total potential revenue (i.e., the product of the total potential audience times the price of a movie ticket). In the diffusion literature (Majahan et al. 1990) the parameter p is traditionally known as the coefficient of external influence. In this case, p relates to the intensity of a movie's marketing campaign. For this reason it will be referred to in the remainder of the article as the *coefficient of publicity*. The parameter q is traditionally known as the coefficient of internal influence. In our setting, it captures the effect of word of mouth from past moviegoers on subsequent movie revenues and will, therefore, be referred to as the *coefficient of word of mouth*.

The difference of equation (1) relative to the traditional Bass model is the addition of the time discounting factor δ . The introduction of time discounting attempts to model the following industry-specific facts: (1) Most movie marketing campaigns occur before or during the first weeks of a movie's release, and, therefore, have a diminishing effect in later weeks. (2) Word of mouth is localized in time; people who watch a movie on week k typically talk about it the most in the immediately following days. Therefore, the contribution of past adopters on current adoption must be discounted by the amount of time that separates the current date from the time of adoption.

Given a training set of movies for which we have available production, ratings, and weekly box office revenue data, our forecasting model can be calibrated and then used in order to forecast future box office revenues of a new movie.

Results

To test the predictive power of our model we divided our data set into two randomly generated subsets of 40 movies each. In the remainder of the paper we will refer to these subsets as data set 1 and data set 2. We calibrated the model using each subset and used it to predict the total revenues of movies in the other subset. The overall fit of the two-parameter model (1) to the weekly revenue vectors of each movie was excellent with an average $R^2 = 0.976$, which says that once we know p and q of a particular movie, we can predict its future weekly box office performance trajectory with an error less than 3 percent.

The fact that the modified Bass equation (1) fits our movie revenue data so well is not surprising. It is well documented that the Bass equation works well with a wide range of phenomena (Bass et al. 1994). What is remarkable, however, is that the estimated

Table 1. List of Independent Variables Considered in Model Selection

Yahoo! Movies Rating Statistics

Average User Rating (<i>week1</i>)	Arithmetic average of all nonzero Yahoo user ratings posted during the movie’s first week.
Adjusted Average User Rating (<i>w1adj</i>)	Weighted average of nonzero user ratings posted by males, females, and users with no declared gender (see text)
Entropy Coefficient (<i>ent1</i>)	Entropy of all nonzero Yahoo user ratings posted during a movie’s first week.
Density of User Ratings (<i>dens1</i>)	$\frac{\text{Total First Week User Ratings}}{\text{First Week Box Office Revenues}}$ A measure of the fraction of moviegoers who posted Yahoo ratings for a given movie during the first week
Ratings Evolution Coefficient (<i>evoll</i>)	$\left(\frac{\text{Total First Week Ratings}}{\text{Total First Weekend Ratings}} \right)^2 \left(\frac{\text{First Week Average Rating}}{\text{First Weekend Average Rating}} \right)^{10}$ A measure of how the initial excitement that surrounds the release of a new movie evolves during the rest of the first week (see text).
Total User Ratings (<i>tot1</i>)	Total number of Yahoo user ratings posted during movie’s first week
Average Critics Rating (<i>critics</i>)	Arithmetic average of Yahoo’s letter grade assessment of critics reviews.

Box Office and Production Data

Box Office Revenues (<i>box1</i>)	Total first week box office revenues for movie
Inverse Revenues per Theater Coefficient (<i>invpth1</i>)	$\left(\frac{\text{First Week Box Office Revenues}}{\text{Number of theaters where movie is shown}} \right)^{-\frac{1}{2}}$ Inverse of a measure of a movie’s first week box office success relative to the producers’ initial expectations.
Budget (<i>bdgt</i>)	Movie production budget
Marketing Costs (<i>mktg</i>)	Estimated movie marketing costs

Note: The functional forms of variables *evoll* and *invpth1* were determined by trial and error to maximize predictive power.

coefficients \hat{p}_i and \hat{q}_i can be predicted with notable accuracy through simple linear regression models that use only first week online ratings and other publicly available movie information.³

We analyzed the relationship of coefficients \hat{p}_i and \hat{q}_i to a large number of statistics derived from first week online ratings, box office, and production data (Table 1) and developed linear regression models for estimating each coefficient.

Coefficient of Publicity

The coefficient of publicity p can be predicted with good accuracy using pure online ratings data. The use of box office and marketing data allows the construction of even more accurate estimators.

Model A. Using online ratings data alone, our two-variable model was able to explain 88 percent and 68 percent of the variation in p in data sets 1 and 2, respectively. The two independent variables are (1) *first week's number of ratings (tot1)*, with a positive coefficient, and (2) *first week's density of ratings (dens1)*, with a negative coefficient. The number of ratings of a given movie is highly correlated to its first week box office revenues. These, in turn, are highly correlated to the publicity surrounding a movie's release. The observation of a strong positive relationship between *tot1* and p is, therefore, not surprising. On the other hand, the negative relationship between *dens1* and p is more perplexing. The density of ratings is a proxy for the fraction of moviegoers who feel compelled to post online ratings. Our data seems to suggest that this fraction is inversely proportional to the publicity surrounding a movie: proportionally fewer people post ratings for movies that are surrounded by high publicity.

A possible explanation for this phenomenon can be based on a "crowding-out" argument from the theory of public goods (Bernheim 1986). Movie ratings can be considered as a public good, in that their posting costs effort to the user but benefits the entire community. In several public good settings (e.g., charities), individuals have been observed to contribute less when there are substantial third-party sources of contributions (e.g., from the government). A variation of this argument can be used to hypothesize that users have a lower propensity to post ratings and reviews for popular movies for which they know that a lot of information exists from alternative sources. Another possible explanation is that the population of online movie raters is a fixed subset of the population, which is still rather small. Therefore, when the number of raters is normalized by the total first week box office revenues, this density measurement decreases as box office revenue increases. It then follows that if box office revenue and publicity are positively correlated, density and publicity are negatively correlated. More research is needed to ascertain the exact reason behind the relationship between *dens1* and p ; nevertheless, this finding provides an interesting glimpse into the complexity of the social dynamics of online communities.

Model B. When box office and production data is included in the list of candidate variables, none of the previous two variables remain significant. In particular, a movie's first-week total revenue (*box1*) is overwhelmingly influential to p ; this variable together with marketing costs (*mktg*) explains 98.6 percent of the variation in p in data set 1 (99.3 percent in data set 2).

Given the set of phenomena (scope of marketing campaign, breadth of initial release, etc.) that the coefficient of publicity is intended to capture, it is not surprising that box office and marketing data (which are direct measures of these phenomena) can lead to more accurate coefficient estimates than online ratings. Nevertheless, the respectable model fit (Adj- R^2 between 68 percent and 88 percent) that was achieved exclusively through the use of online ratings data provides evidence for the value of online ratings as a proxy of sales and marketing efforts. This could prove useful in competitive analyses of industries where sales and marketing data are not publicly available.

Coefficient of Word of Mouth

Reconfirming our expectations, the coefficient of word-of-mouth q is well explained by first week online ratings statistics. Adding box office measures only marginally improved the model.

³We experimented with several variations of equation (1), including a simple Bass model without time discounting. The use of time discounting was not essential in fitting the Bass equation to the weekly revenue vectors of our data set. However, time discounting was crucial in order to obtain coefficient estimates \hat{p}_i and \hat{q}_i that had meaningful relationships with (and therefore could be estimated by) first-week online ratings and box office data.

Model A. Using online-ratings alone, our three-variable model was able to explain 53 percent and 48 percent of the variation in q in data sets 1 and 2 respectively. The following is a discussion of the three independent variables, in descending order of significance.

1. The first week's *adjusted average user rating* ($w1adj$) is a weighted average of ratings submitted by males, females and users of undeclared gender. The weights were determined experimentally to maximize model fit:

$$w1adj = 0.53 \times (FemaleRatings) + 0.05 \times (MaleRatings) + 0.42 \times (NoGenderRatings)$$

The adjusted average $w1adj$ was more informative than the raw arithmetic average of ratings ($week1$). This is not surprising, given that the demographic breakdown of Yahoo! Movie users (75 percent male, under 35) in our data set is skewed compared to the national average. An interesting observation is that ratings submitted by females carried substantially more weight than ratings submitted by males in terms of predicting the coefficient of word of mouth. This finding persisted in ratings submitted in later weeks and merits further attention.

2. By analyzing the evolution of Yahoo user ratings over time, we discovered that they exhibit a systematic upward bias during the first weekend of a new movie's release. We hypothesize that this bias is due to the fact that a significant fraction of people who choose to watch a new movie during its first weekend are self-selected (i.e., have a special interest for the movie's genre, are devoted fans of the movie's stars, etc.) and thus have a higher propensity to like it than the average moviegoer. The *evolution coefficient* ($evol1$) is a measure of how fast this initial excitement about a movie (proxied by the product of the number of ratings times the average valence of ratings) declines during the remainder of the first week. The higher the value of $evol1$, the lower the decline of excitement about the movie relative to the first weekend. This measure turned out to be the second most significant predictor of the coefficient of word of mouth in our set of variables. The significance of the evolution coefficient in predicting a movie's coefficient of word of mouth demonstrates that valuable information can be extracted from studying the dynamics of online feedback communities.
3. The *total number of user ratings* ($tot1$) submitted during the first week turned out to be significant for predicting the coefficient of word of mouth, although less so than for predicting the coefficient of publicity. We believe that the presence of this variable in both models indicates that the number of first week moviegoers relates to both a movie's publicity campaign as well as to the strength of initial word of mouth about the movie.

Model B. The addition of box office and production data to the set of candidate variables increased the ability of our model to explain the variation of q in data sets 1 and 2 to 70 percent and 67.5 percent respectively. A movie's adjusted average rating ($w1adj$) and evolution coefficient ($evol1$) remained significant in this model as well. Among all possible measures of box office, there was only one variable significant in explaining q 's variation: $invpth1$ defined as the inverse of the square of *first week's revenue per theater*. We consider the first week's revenue per theater to be a measure of the financial success of a movie relative to the studio's pre-release expectations (these expectations determine the number of theaters on which the movie is initially released). Studios use sophisticated pre-release models that consider a variety of factors in making this decision (De Silva 1998; Eliashberg et al. 2000; Litman 1983; Litman and Kohli 1989; Sochay 1994; Zufreyden 1996). Word of mouth is probably the most important factor that studios *cannot* accurately predict beforehand. Our hypothesis, therefore, is that the variation in revenue per theater is correlated with the strength of word of mouth about the movie. This hypothesis is confirmed by our data which shows a strong negative relationship between the *inverse* of this measure and the coefficient of word of mouth.

We were somewhat surprised to find that the predictive power of the *adjusted average user rating* ($w1adj$) was greater than that of *average critic reviews* ($critics$) on both data sets. Furthermore, the $critics$ variable did not pass our variable selection criteria on any of our models (e.g., it did not substantially increase the adjusted R^2 of any model and/or exhibit substantial multicollinearity with some other model variable). The tentative conclusion is that, when large numbers (~312 per movie) of online ratings are properly weighted and assessed, they can provide more information than a small number (~13 per movie) of expert reviews. Although specific to our context, this finding supports the viewpoint that online forums are emerging as a valid alternative source of information, replacing our societies' traditional reliance on the "wisdom of the specialist" by the "knowledge of the many."

Forecasting Accuracy

The ultimate objective of our model is to help studios forecast a movie's future box office revenues from first week's rating and box office data. To test the predictive accuracy of our approach, we calibrated two pairs of models (each pair consisting of Model A and Model B), one using data set 1 and another using data set 2. We then used each model to derive estimates of coefficients

p and q for movies in the *other* data set. Finally, we substituted those coefficients into equation (1) and performed numerical integration to derive forecasts of each movie's future week revenues.

With the exception of a small number of movies for which our models get it very wrong, the models' predictions are remarkably accurate. The distribution of each model's errors is consistent across the two data sets. Model A achieves absolute prediction errors lower than 25 percent approximately 45 percent of the time and errors lower than 50 percent approximately 70 percent of the time. The more accurate Model B achieves absolute prediction errors lower than 25 percent approximately 70 percent of the time and errors lower than 50 percent approximately 90 percent of the time.

Movies with unusually high prediction errors correspond to "sleeper" movies such as *My Big Fat Greek Wedding* and *Chicago*. Such movies are characterized by relatively low marketing campaigns and a slower box office revenue buildup, primarily fueled by word of mouth. Given that the parameters of our model were calibrated using a set of movies that contained a majority of blockbuster movies, it is not surprising that the model fails to predict accurately the revenue trajectory of sleeper movies. Nevertheless, in theory at least, the diffusion equation should be valid for sleeper movies as well. In future work we will calibrate the model using data sets that contain larger numbers of sleeper movies to test this point.

Conclusions

Online review sites are widespread on the Internet and rapidly gaining in popularity among consumers. Nevertheless, the business value of such information systems to organizations has, to date, not been established. This paper contributes in this direction by studying the value of online movie reviews in forecasting motion picture revenues. Inspired by the Bass model of product diffusion, we develop a simple and notably accurate motion picture revenue-forecasting model, based on statistics of online movie reviews posted by users on Yahoo! Movies during the first week of a new movie's release.

Apart from helping a company forecast demand and plan its own actions, we believe that the techniques introduced in this paper have the potential to play an important role in competitive analysis. In a lot of product categories, sales and marketing budgets are secret information and therefore competitive analysis has been a difficult task. The vast amounts of consumer ratings that are publicly available on the Internet have the potential to fundamentally change this.

Our future work will explore enhancements that further improve the predictive power of our model. Initial experiments indicate that consideration of competition from other simultaneously released movies and calibration of separate models for different movie genres can improve forecast accuracy. Our most important long run goal, however, is to apply the techniques explored in this paper to other industries as well, in order to better understand the impact of online word of mouth on product diffusion and the competitive implications of this phenomenon for firms and online community operators.

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